Study Of Pool Fire Heat Release Rate Using Video Fire Detection

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ABSTRACT

To provide fire safety for high performance buildings, various types of fire/smoke detection systems are developed. Video fire detection is one of the important aspects in the development of fire detection system. It is particularly useful in large spaces with high headroom and buildings with cross ventilation design where traditional spot type smoke detection methods may not be effective. For the development of video fire detection system, spatial, spectral and temporal parameters are used to identify the fire source. One of the parameters captured by the video fire detection system is the flame height. With the information of flame height, real time heat release rate of fire can be estimated which is a very important parameter in determining the smoke generation rate and fire severity. Such information is very important in assisting evacuation and smoke control. In this study, experiments of pool fires with different pool diameters of 100mm, 200mm, 300mm and 400mm are conducted in the fire chamber of the laboratory in Department of Building Services Engineering, The Hong Kong Polytechnic University. The flame images, room temperatures and mass loss rates of the fuel are measured. The flame images are segmented using multi – threshold algorithm in a modified Otsu method and Rayleigh distribution analysis (modified segmentation algorithm). The algorithm use the optimum threshold values calculated to extract the pool fire images from a video sequence. After segmentation, flame height information can be obtained. In addition, other flame characteristics are also used for recognizing the flame region including flame color, flame light intensity, flame shape, and flicker frequency. Once the flame height is identified by the system, the heat release rate can be estimated using the equation developed by McCaffrey. The calculated heat release rates are then compared with measured heat release rate data. The results show that using flame height image for estimating real time heat release rate is promising.

1. INTRODUCTION

Building fire is a complex phenomenon. Fire and smoke spread within the building can be affected by various factors such as the geometry, dimension, layout and usage of the building. In order to provide fire protection in the building, it is very important to detect fire at its early stage. The most common fire and smoke detection methods include the use of point/spot type detectors (i.e. ionization smoke detectors, photoelectric detectors, heat detectors), line type detectors etc. These detection methods based on the use of fire signatures such smoke, heat. However, these detection methods have some significant drawbacks including delay in smoke and fire detection especially in large space such as atrium.

For heat detection, the heat released at the early stage of fire in an atrium would not be able to heat up the large amount of air to the flashover temperature of 500 °C. It has been demonstrated that the air temperatures will be very low compared to flashover temperatures due to air entrainment into the smoke plume. Experimental studies have shown that the smoke temperature (away from the flame) in a 26.3 m atrium with a 1.3 MW methanol fire was less than 50 °C. In some cases, the smoke may not be able to reach the ceiling of the atrium. Similar problems can be encountered in using smoke detectors.

The new development trend in early smoke and fire detection method is based on the video image processing technique. It can overcome the problems associated with conventional fire and smoke detectors such as the constraints in detection distance and area or disturbances from the surroundings. Moreover, it can provide other useful information such as the fire size and location of the fire. If the fire can be exactly located before spreading to adjacent area, it can be controlled or suppressed at the early stage and the damages can be minimized.

Besides atrium, video fire detection is particularly useful in different kind of buildings such as electrical and mechanical plant room, warehouses, atria, aircraft cargo, hangars, tunnels and some high performance buildings with large internal void. Therefore, video fire detection systems are proposed.

For the development of video fire detection, spatial, spectral and temporal parameters are used to identify the fire source (Healey, et al., 1993). One of the important parameters can be captured by the video fire detection is the flame height. Based on the image data of flame height, heat release rate (HRR) of fire can be estimated. HRR is a very important parameter in determining the smoke generation, fire severity. It can also be used to assist evacuation and develop efficient smoke control systems. HRR can be measured using mass loss rate and oxygen consumption method. These two methods are useful in research studies. However, they not feasible in practical building fire detection as the mass loss rate of the fuel and the oxygen consumed in the fire cannot be measured in a real building fire. Fortunately, various empirical equations correlating flame height and HRR were developed by different fire researchers. By using these empirical equations, HRR in a real building fire can be estimated by the flame height information captured by video fire detection system.

The image data of flame height is recorded by the digital camera. To obtain the flame height information, flame shape must be segmented from image captured by the video fire detection system. Various methods can be used to segment the flame image from the video images. One of the image segmentation methods was published in 1979 called the Otsu method. It can segment different objects from the gray scale images using the optimum threshold value (Otsu, 1979). The calculation of threshold value is considered fairly simple and convenient. In current study, the analysis of flame image data was conducted by modified Otsu method as the segmentation results for the flame image is not very satisfactory using the traditional Otsu method. Figure 1 illustrates the general procedure of segmentation analysis.

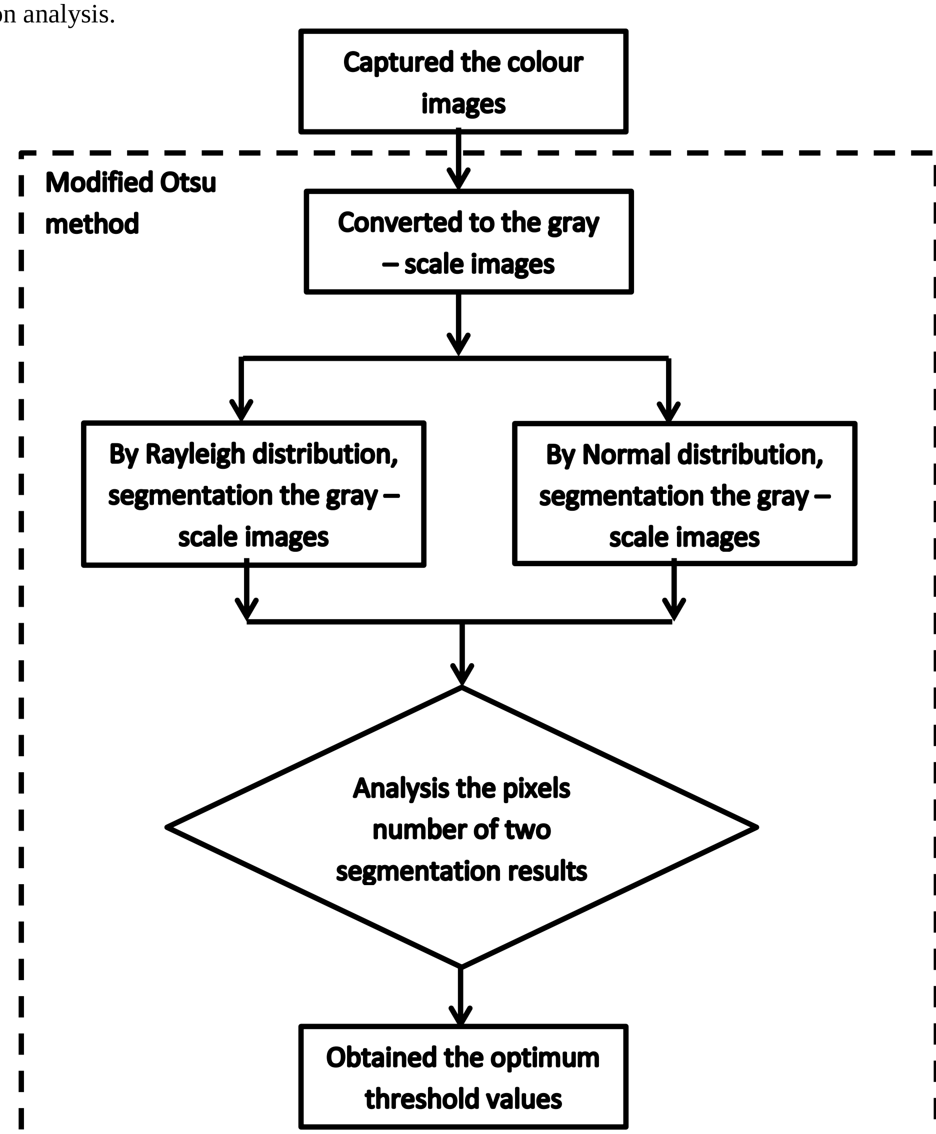


Figure 1: General procedure of segmentation analysis

Based on the optimum threshold value extracted from the gray – scale flame images, the flame height can also be estimated. To recognize the flame image from video images and segment the flame from background object, analysis of flame characteristics are very important. The fire characteristics are not only flame height but also the flame color, flame light intensity, flame shape and flame flickering frequency. These characteristics are very useful in recognizing the fire in video fire detection. After obtaining the flame height from the video images, the mean flame height of the pool fire can be obtained. Then the mean flame height can be used to estimate the heat release rate (HRR) of the pool fire using the empirical equation developed by McCaffrey (Heskestad, 2002). Equation 1 illustrates the McCaffrey equation.

$$\frac{L}{D} = -1.02 + 3.7\dot{Q}^{*2/5} \tag{1}$$

$$\dot{Q}^{*} = \frac{\dot{Q}}{\rho_{\infty} c_p T_{\infty} \sqrt{gD} \cdot D^2} \tag{2}$$

where L is the mean flame height (m), D is fire pool diameter (m), $\dot{Q}^{*}$ is the dimensionless heat release rate (-) used in the equation, $\dot{Q}$ is the total heat release rate (kW), ρ_{∞} is the ambient density (kg/m^3), c_p is the specific heat of air at constant pressure (kJ/kg K), T_{∞} is the ambient temperature (K) and g is acceleration due to gravity (m/s^2).

Based on the equation 1 and 2, the HRR of the pool fire can be estimated using the mean flame height and the fire pool diameter.

In this study, a series of experiments with 100mm, 200mm, 300mm and 400mm pool fire diameters were conducted to obtain the HRRs using mass loss rate calculation. The HRRs are then used to compare with the HRRs estimated from video images and equation 1.

2. LITERATURE REVIEW OF THRESHOLD ANALYSIS METHODS

A review of the literature relating to the threshold analysis methods in video fire/smoke detection reveals that two major analysis methods are able to obtain the threshold values for image segmentation.

a) Colour images processing analysis methods (Threshold of red colour component)
b) Statistical analysis methods (Mean and standard deviation).

The threshold analysis can also make use of different parameters such as the fire features including the color, textures, geometry, flickering frequency and motion. Foo (Foo, 1996) suggested that the statistical analysis relating to threshold scenario can be used in the machine vision system. The threshold levels can be used for discrimination the fire from a non – fire events by the histogram analysis method. In video fire/smoke detection, the ratio of reflectance in two channels $(R1, R2)$ and the brightness temperature (BT) can also be used as the threshold criteria (Li, et al., 2001). Color image processing analysis method of video fire detection, the threshold of color saturation (S_T) and red color of fire (R_T) were also used as important criteria (Chen, et al., 2003) (Chen, et al., 2004) (Podrzaj & Hashimoto, 2008).

In discrimination of the fire image, the threshold value of white pixels ratio (r_w) can also be used (Horng, et al., 2005). In statistical color model, global threshold (τ) was used. The function of the global threshold is used to monitor the state of corresponding pixels $(S(x), S(x,y))$ (Celik, et al., 2006) (Celik, et al., 2006). In some threshold analysis for video fire detection, alarm threshold (L_{th}) was proposed. The parameter of alarm threshold is based on the luminosity (L) (Owrutsky, et al., 2006). The threshold value is not only useful for discrimination of fire or non – fire image but it can also be used to extract the flame images. The parameter of threshold (Th) was used to monitor the luminescent objects (Ono, et al., 2006). Analysis and defined four threshold (T) decision parameters were proposed in video fire detection including (Toreyin, et al., 2006)

a) Moving region detection
b) Fire color pixels detection
c) Temporal wavelet analysis
d) Spatial wavelet analysis

The values of two threshold values $(\mu_{low}(x))$ and $(\mu_{high}(x))$ was proposed in the fire region (Ω_{ROI}). Six main fire features was combined to build the fire indicator (Marbach, et al., 2006).

a) Luminance of the active pixels
b) Frequency of the luminance of the active pixels
c) Amplitude of the luminance of the active pixels
d) The number of active pixels
e) The number of saturated pixels
f) The number of fire colour pixels

In the analysis of the threshold value, the angle of flame region (Th_{angle}) was obtained in video surveillance system (Lai, et al., 2007) (Lai & Yang, 2008).
In the selection of appropriate threshold values for video fire/smoke detection, two different approaches are used. The major algorithm of video fire detection was to obtain flame color information.

Three different image processing techniques for video fire detection are proposed: (Lee & Han, 2007)

a) movement detection $(A_{TN}(x,y))$
b) edge detection $(E(x,y))$ by Sobel mask
c) color information $(C(x,y))$

In the analysis of color space model, heuristic fixed threshold values were proposed. The heuristic fixed threshold value is able to replace by Binary Background Mask (BBM) (Cho, et al., 2008).
Statistical analyses of the fire images characteristics were also proposed, the threshold to the image characteristics include the fire (RGB) color pixels (f_R, f_G, f_B), geometry (λ_A) and motion of fire region (λ_C) (Borges, et al., 2008).

Accumulative smoke motion model was proposed in video smoke detection. Analysis the smoke and non – smoke pixels, predetermined threshold of chrominance (C) and intensity (I) are used (Yuan, 2008).

In analyzing the smoke in tunnel, two thresholds (th_2, th_3) are proposed. Threshold 1 (th_2) is to use the numerical equation to calculate the input images $(I_N(x,y))$ and background $(T(x,y))$ images differently. Threshold 2 (th_3) is used to analyze the moving region by motion history image (MHI) (Han & Lee, 2009).

Two threshold analysis (T_m, T_a) methods for detection the flame and smoke were proposed, including the changed region and feature fusion. The changed regions were used to analyze the flame colour and shape of smoke (Wang, et al., 2009). Feature fusion was used to estimate the threshold value.

Three thresholds (T, T_m, R_T) were considered in fast video flame detection. The first threshold (T) is the background and foreground analysis with the Gaussian mixture model. The second threshold (T_m) is the absolute difference of observation value of pixel $(\vec{X}_{m,t})$ and the average of the mean vectors $(\vec{u}_{m,t})$. The third threshold (R_T) is the global threshold of red color component (Chen, et al., 2009).

Artificial Neural Network (ANN) was also proposed to train the computer to recognize the flame images. During the training, the threshold value was calculated to adjust the relation between the input and output samples in the Artificial Neural Network (ANN) (Zhang, et al., 2009).

Different algorithm such as Hybrid Clustering Algorithm was also proposed to estimate the threshold values (Chakraborty & Paul , 2010). The Hybrid clustering algorithm is proposed to use two clustering method (Hierarchical clustering and Partition clustering) to calculate the threshold values.

There are also four threshold values proposed $\left(T_{FD}, T_{BD}, \tau(DI), T_{SI}\right)$ for image segmentation. The threshold of frame difference (T_{FD}) was created the binary frame difference map by CIE L*a*b* color space. The threshold of background difference (T_{BD}) was created the binary background difference map also by CIE L*a*b* color space. The dynamic threshold $\tau(DI)$ was proposed to improve the fixed – threshold setting for reduce the false alarm rate by the mean (μ) and standard deviation (σ) of pixel values. The threshold of stationary index (T_{SI}) was proposed to detect the moving pixels from the binary frame difference map by the video fire detection system (Celik, 2010).

3. METHODOLOGY

In this study, the video fire detection has two major parts (segmentation and recognition).

In segmentation:

a) The color images are converted to gray scale images. RGB and YIQ color space model is used
b) The intensity histogram can be generated from the gray scale images for numerical analysis
c) From the intensity level of the gray scale images, the binary images is segmented by modified Otsu method. In the binary images, the flame region is marked as “0” and the background region is marked as “1”.

Recognition:

a) From the flame region of binary images, the flame height can be estimated.
b) By the estimation of flame height and empirical equation of heat release rate (HRR), the pool fire HRR can be estimated.

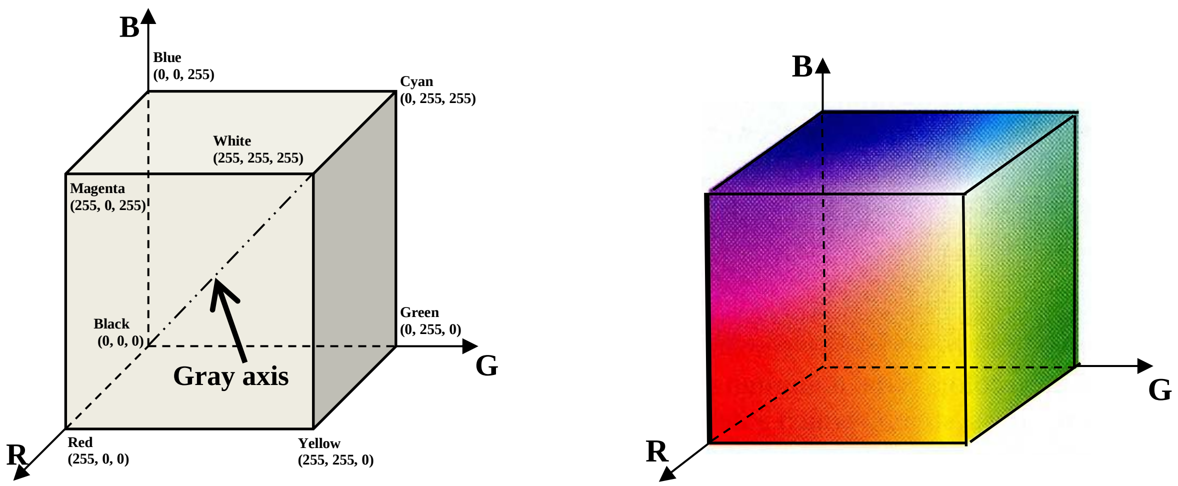
In the following presents the detail of experiment including the segmentation and recognition algorithm.

The color images are converted into the gray scale images. Two approaches are used. First, the intensity level of images is calculated. Generally the color images are first converted to gray scale images. The YIQ color space model is the common transformation method provided in MATLAB.
The matrix formula of YIQ color space model is illustrated in equation 3. Based on the matrix formula, the calculation method of intensity level is illustrated in equation 4. $Y(x, y)$ denoted the intensity levels in x and y coordinate.

$$\begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.596 & -0.274 & -0.322 \\ 0.211 & -0.523 & 0.312 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} Y \\ I \\ Q \end{bmatrix} \tag{3}$$

$$Y(x, y) = 0.299 \times R(x, y) + 0.587 \times G(x, y) + 0.114 \times B(x, y) \tag{4}$$

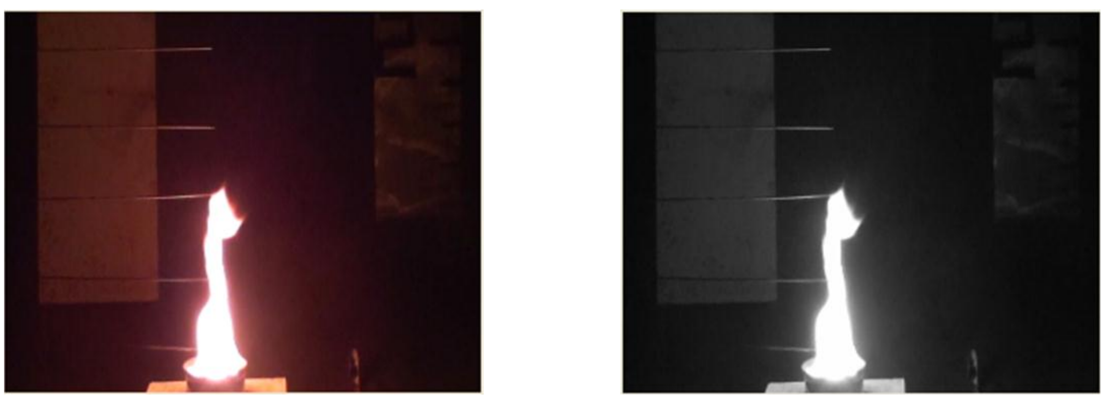
Second, when each coordinate of RGB components have equal intensity level (Y), conversion to a gray scale images can be generated. Figure 2 illustrates the schematic of RGB components. Figure 3 illustrates the experimental results (a) colour images (b) gray scale images.



Schematic of colour cube

Colour cube

Figure 2: Schematic of RGB colour space model



(a) Colour images

(b) Gray scale images

Figure 3: (a) colour images convert to (b) gray scale images

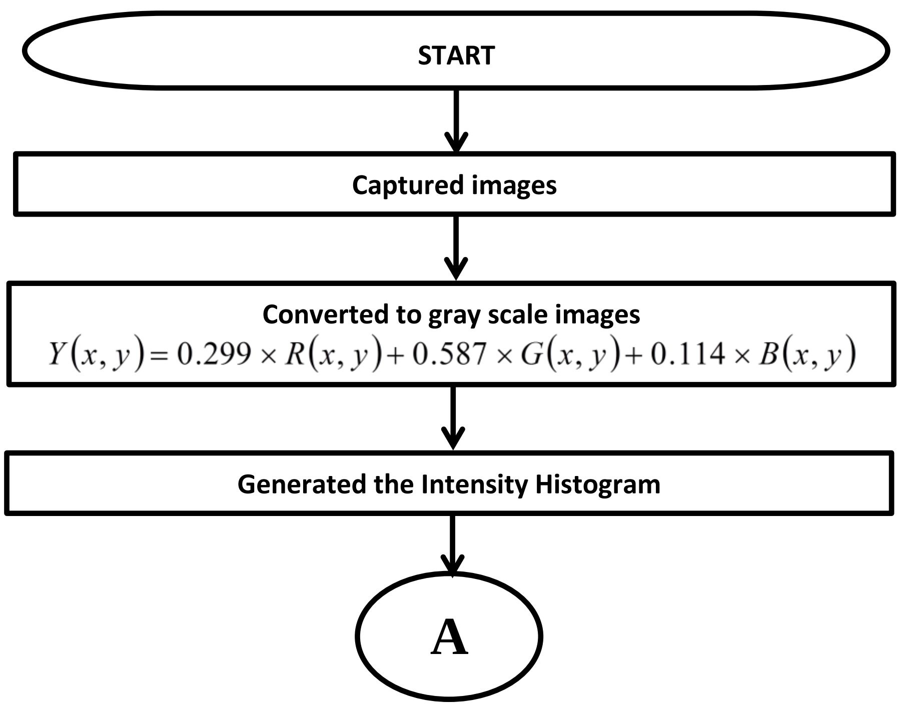
Using statistical analysis method, the intensity histogram can be generated after the gray scale images have been obtained. The luminance quality relates directly to the intensity levels. Numerical analysis of the gray scale images reveal the intensity level indicated by each pixel. The resulting intensity histogram then presents the luminance characteristics of gray scale images. The horizontal axis (x – axis) represents intensity levels from 0 to 255 (256 intensity levels). The vertical axis (y – axis) represents pixel frequency (number of pixels). Figure 4 illustrates the gray scale image of the fire and the intensity histogram

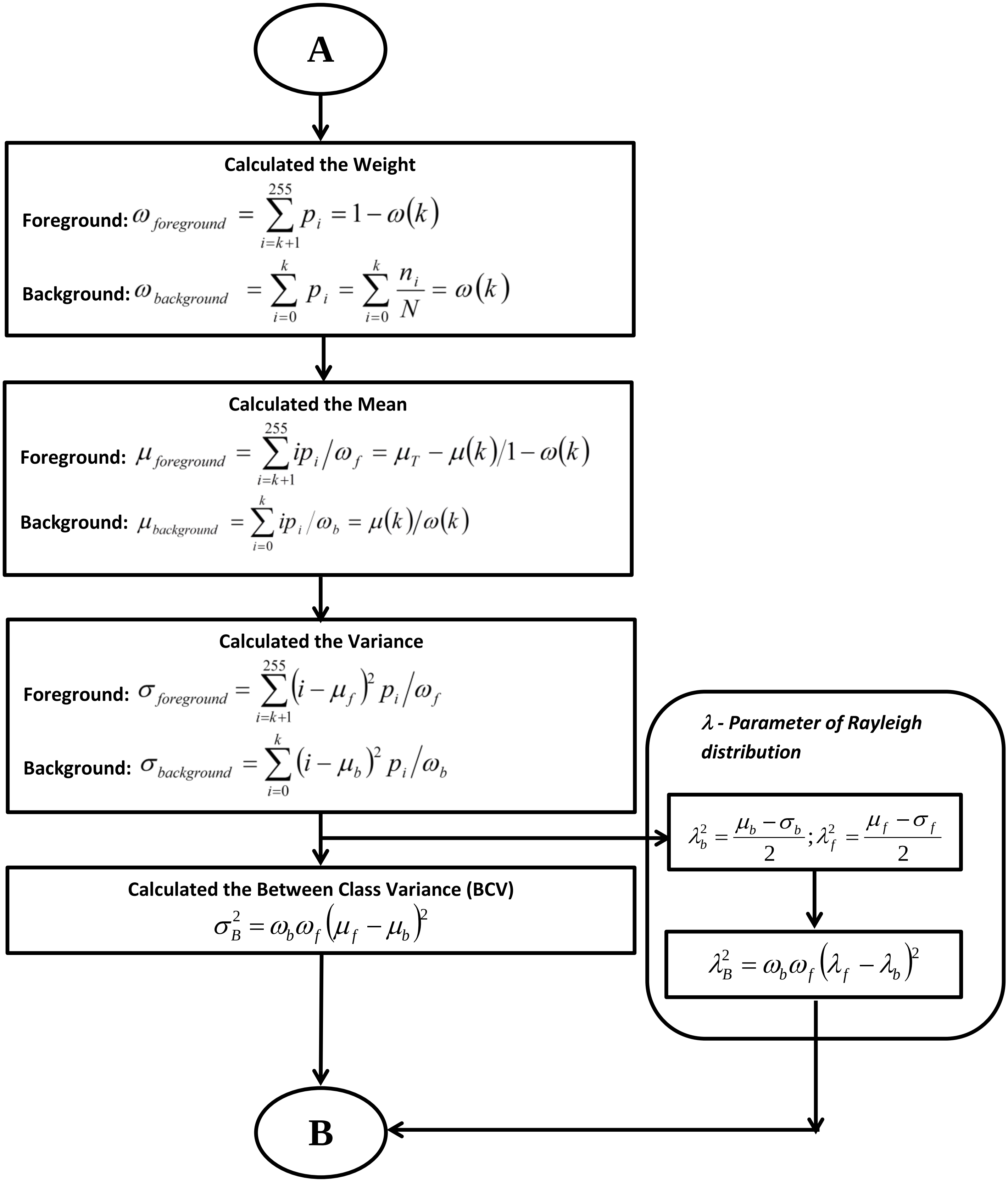
(a) Gray scale image (b) Intensity histogram

Figure 4: (a) Gray scale image and (b) Intensity histogram

The intensity histogram reflects the intensity levels based on the gray scale images data. The gray scale fire images and the intensity histogram present the flame level intensity against the background environment.

The objective of segmentation is to extract the flame region (foreground) from the background. The method is referred to as modified Otsu method. Otsu's method determines the threshold value by analyzing the intensity level. The range of intensity level is from 0 to 255. The optimum intensity value is within this range. The modified Otsu method combines two steps: 1. Multi – threshold method (Otsu, 1979) and 2. Rayleigh distribution based Otsu's method (Wan, et al., 2010). The segmentation of the modified Otsu method is better than the traditional Otsu's method for the selection of the optimum threshold value because the modified method can obtain more than one threshold value (multi – threshold values). The selection criteria of optimum threshold value in segmentation are able to automatically segment the flame region (foreground) and background region based on pixel number in the flame region. Figure 5 illustrates the flow diagram of modified Otsu method.




A
Calculated the Weight
Foreground: $\omega_{foreground} = \sum_{i=k+1}^{255} p_i = 1 - \omega(k)$
Background: $\omega_{background} = \sum_{i=0}^{k} p_i = \sum_{i=0}^{k} \frac{n_i}{N} = \omega(k)$
Calculated the Mean
Foreground: $\mu_{foreground} = \sum_{i=k+1}^{255} ip_i / \omega_f = \mu_T - \mu(k)/1 - \omega(k)$
Background: $\mu_{background} = \sum_{i=0}^{k} ip_i / \omega_b = \mu(k)/\omega(k)$
Calculated the Variance
Foreground: $\sigma_{foreground} = \sum_{i=k+1}^{255} (i - \mu_f)^2 p_i / \omega_f$
Background: $\sigma_{background} = \sum_{i=0}^{k} (i - \mu_b)^2 p_i / \omega_b$
Calculated the Between Class Variance (BCV)
$\sigma_B^2 = \omega_b \omega_f (\mu_f - \mu_b)^2$
λ - Parameter of Rayleigh distribution
$\lambda_b^2 = \frac{\mu_b - \sigma_b}{2}; \lambda_f^2 = \frac{\mu_f - \sigma_f}{2}$
$\lambda_B^2 = \omega_b \omega_f (\lambda_f - \lambda_b)^2$
B

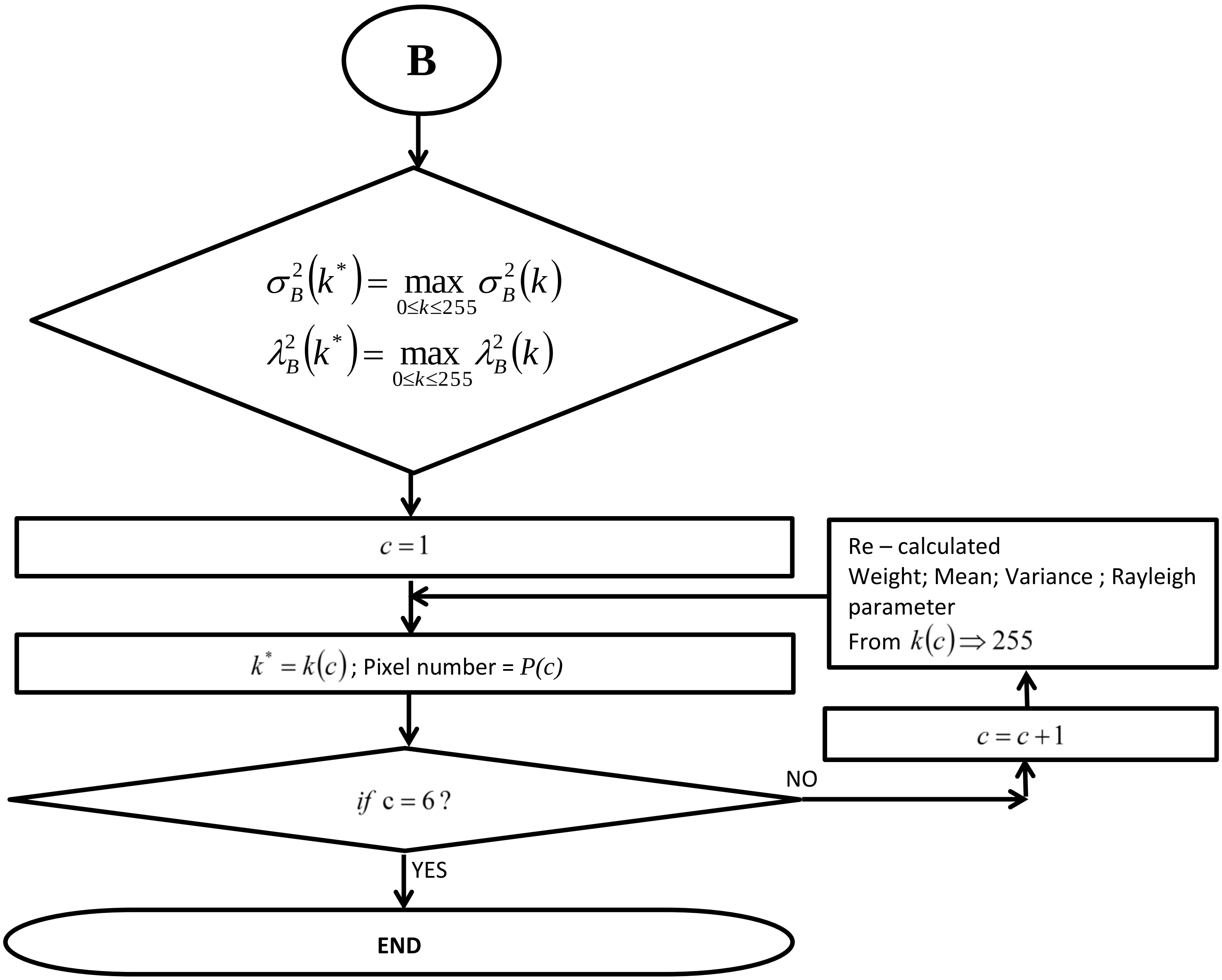
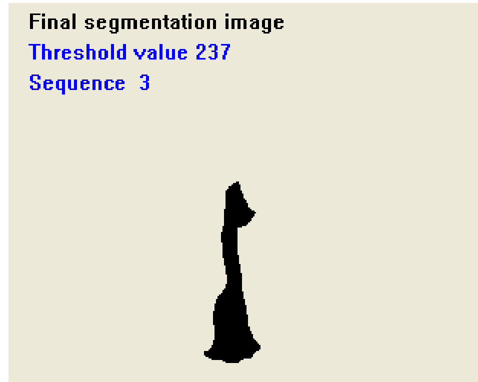


Figure 5: Calculation flow diagram of modified Otsu method

Figure 6 illustrates the numerical results and the segmentation images. Based on the numerical results of modified Otsu method, the same pixels number is 1,953 at the sequence number 3. The optimum threshold value is 237 (between 0 – 255) so the segmentation of flame region can be obtained.

Normal Threshold	Pixel	Rayleigh Threshold	Pixel
[1] 125	[1] 3314	[1] 171	[1] 2672
[2] 207	[2] 2123	[2] 215	[2] 2069
[3] 237	[3] 1953	[3] 237	[3] 1953
[4] 248	[4] 1891	[4] 249	[4] 1878
[5] 252	[5] 1839	[5] 252	[5] 1839
[6] 253	[6] 1817	[6] 253	[6] 1817

(a) Numerical results



(b) Segmentation images

Figure 6: (a) Numerical results by modified Otsu method (b) Segmentation images

When the segmentation flame images are overlap on the original color images, the modified Otsu method is able to segment the clear flame region in this case to estimate the flame height. Figure 7 illustrates the overlap result.

Figure 7: Segmentation images overlap on the original colour flame images

From the segmentation images, flame height can be obtained by digital images. Generally, the digital images can be obtained the bottom level (y_B) of flame region and top level (y_T) of flame region. From the bottom level and top level of flame region is able to obtain the number of pixels to the flame height. The calculation of flame height in images is illustrated in Equation 3. Based on the image height, the actual flame height can be used to calculate by the relevant equation of focal length (f), object location (d_o) and image distance (d_i). The algebraic equations for calculation the actual flame height are obtained as follows: (Mohd Shafry, et al., 2012)

From the operating guide of digital camera, complementary metal–oxide–semiconductor (CMOS) Sensor ¼ type is used in the experimental study. The image sensor size is 3.6mm (width) and 2.7mm (height) (Clark, 2005). The no. of images pixel is 300 (width) and 240 (height) so the pixel size of images are 0.012mm (width) and 0.01125mm (height)

$$\text{Flame height in images} = \text{no. of flame pixels}\left(\mathrm{y_B} - y_T\right) \times \text{pixel size of images} \tag{5}$$

$$\frac{1}{f} = \frac{1}{d_i} + \frac{1}{d_o} \tag{6}$$

$$d_i = \frac{(f \times d_o)}{(d_o - f)} \tag{7}$$

$$D_c = \sqrt{L_c^2 + H_c^2} \tag{8}$$

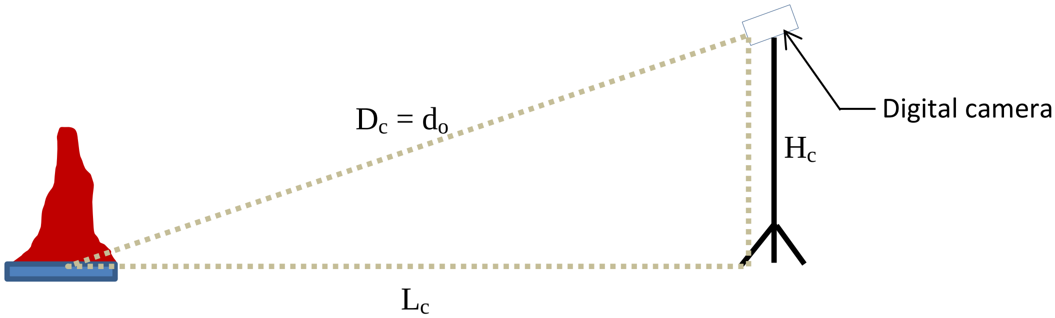


Figure 8: Schematic of Camera and fire pool setup

$$h_o = h_i \times \frac{d_o}{d_i} \tag{9}$$

where h_i is flame height in images, h_o is the actual flame height, L_c is horizontal distance from fire to camera, H_c is camera height. After obtaining the flame height from the digital images, the HRR can be estimated by the McCaffrey equation because the flame region depends on HRR (Q).

To test whether the video fire detection method can be used to estimate the hrr of the pool fires, a series of experiments were conducted. Four sizes of pool were used for recording the fire images including 100mm, 200mm, 300mm and 400mm. Table 9 illustrates the actual size of pool diameter. Figure 10 illustrates the typical four sizes of pool diameter. To ignited the pool fire was used the industrial grade propanol. Figure 11 illustrates the fuel properties. For more accuracy to estimation the heat release rate of the fire, the information of fuel properties are required to estimate the total heat release rates (HRR) from the flame height and pool diameter.

Typical pool diameter	**100mm**	**200mm**	**300mm**	**400mm**
A	115	197	340	410
B	54	60	65	80
C	102	197	330	410

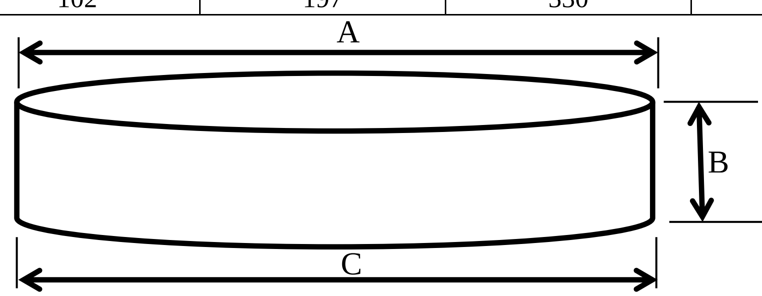


Figure 9: Actual size of pool diameter

	
100mm	200mm
	
300mm	400mm

Figure 10: Four sizes of pool diameter

<u>Fuel Properties</u> **2 – Propanol industrial grade** **Molecular formula:** C_3H_8O **Molecular weight:** 60.10 g/mol **CAS Registry Number:** 67 – 63 – 0 **Density:** 786 g/cm^3 at 20 ^{o}C **Heat of combustion:** **(Gross value):** 33.61MJ/kg **(Net value):** 30.68 MJ/kg. (Anon., 2014)	

Figure 11: Fuel Properties

The flame images were recorded by the digital camera and the flame images is recorded in the Bitmap file format (BMP). The digital images analysis algorithm was used by the Visual C++. Figure 10 illustrates the experimental results of flame height analysis for four different pool diameters.

Table 1: Experimental results of flame height analysis

Fuel		2 – Propanol			
Pool diameter	mm	102	197	330	410
Fuel	mL	100	800	800	800
Mass loss rate	g/s	0.1264919	0.5157317	1.6350179	2.0463882
Molar coefficient	kJ/mol	2220	2220	2220	2220
Molar weight	g/mol	60.1	60.1	60.1	60.1
Heat of combustion	kJ/g	36.938436	36.938436	36.938436	36.938436
Combustion efficiency		0.7	0.7	0.7	0.7
HRR (Based on MLR)	kW	3.2706883	13.335226	42.276503	52.913266
Number of images	nos.	30	30	30	30
Mean flame height	mm	183.63	283.80	462.16	667.80
Pool diameter	m	0.102	0.197	0.33	0.41
Revised HRR (Based on images results)	kW	1.6579322	6.1108622	21.299584	45.909748

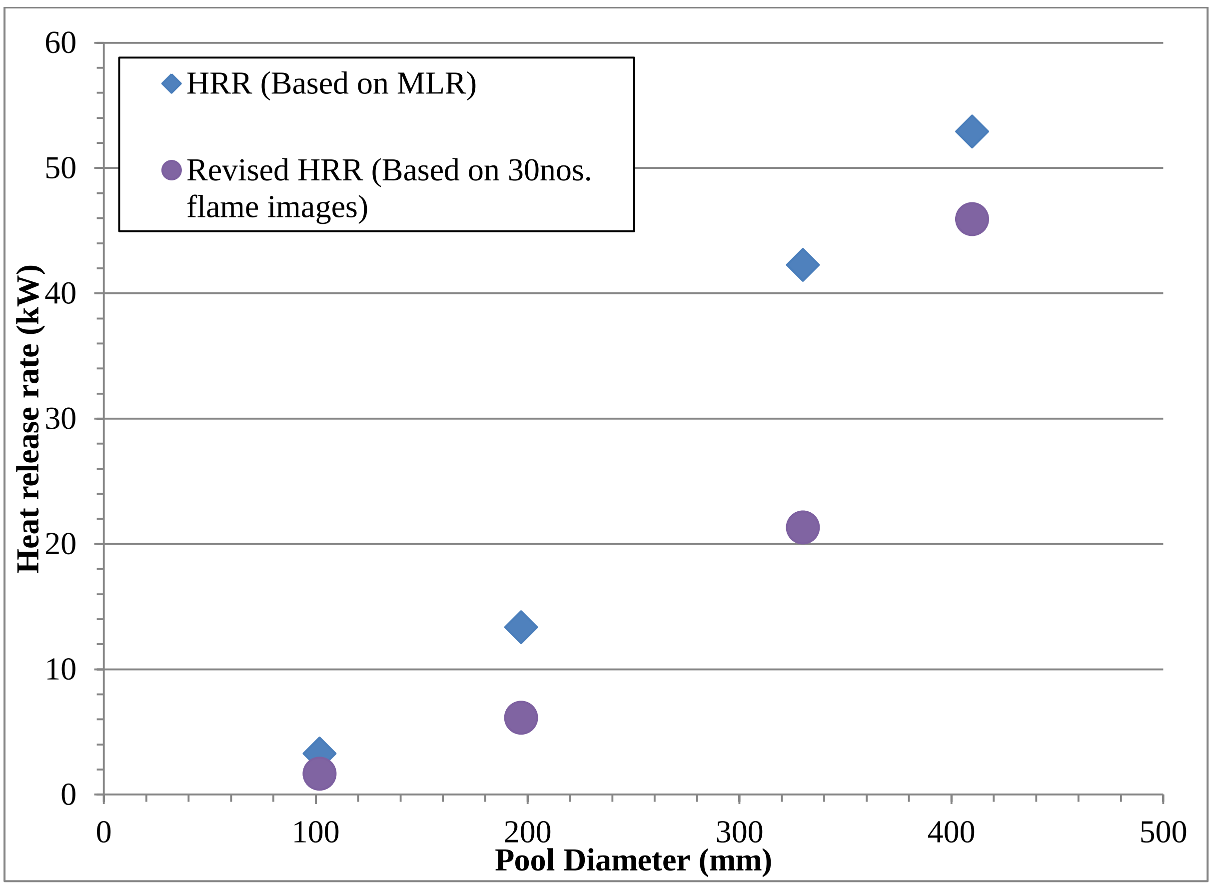


Figure 12: Comparison of the heat release rates of pool fires

4. CONCLUSIONS

In the current study of video fire detection system, we found that it is possible to predict the heat release rate of fire based on the image data and empirical equations.
In the experimental results, when the color flame images are converted to the gray scale images by the color transformation of image processing techniques, the intensity histogram of gray images can be generated. The distribution of intensity level to the fire images can be comprehended from the histogram. From the difference of intensity level to the image pixels, the segmentation can be divided the flame region and the background in specific environment by modified Otsu method.
Though the flame shape and the flame height varied at different time, more analysis of the flame height information can enhance the results in future.

REFERENCES

Anon., 2014. Appendix C - Fuel Properties and Combustion Data. In: *SFPE Handbook of Fire Protection Engineering.* United States of America: National Fire Protection Association, pp. A - 39.
Borges, P. V. K., Mayer, J. & Izquierdo, E., 2008. *Effective Visual Fire Detection Applied for Video Retrieval.* Switzerland, EURASIP, pp. 25 - 29.
Celik, T., 2010. Fast and Effective Method for Fire Detection Using Image Processing. *ETRI Journal,* pp. 881 - 890.
Celik, T., Demirel, H. & Ozkaramanli, H., 2006. *Automatic Fire Detection in Video Sequences.* Italy, s.n.
Celik, T., Demirel, H., Ozkaramanli, H. & Uyguroglu, M., 2006. Fire Detection in Video Sequences Using Statistical Color Model. *IEEE,* pp. II-213 - II-216.
Chakraborty, I. & Paul , T. K., 2010. *A Hybrid Clustering Algorithm for Fire Detection in Video and Analysis with Color based Thresholding Method.* s.l., IEEE Computer Society, pp. 277 - 280.
Chen, J., He, Y. & Wang, J., 2009. Multi - feature fusion based fast video flame detection. *Building and Environment.*
Chen, T. H., Kao, C. L. & Chang, S. M., 2003. An Intelligent Real - TIme Fire Detection Method Based on Video Processing. *IEEE,* pp. 104 - 111.
Chen, T. H., Wu, P. H. & Chiou, Y. C., 2004. An Early Fire - Detection Method Based on Image Processing. pp. 1707 - 1710.
Cho, B. H., Bae, J. W. & Jung, S. H., 2008. *Image Processing - based Fire Detection System using Statistic Color Model.* s.l., IEEE Computer Society, pp. 245 - 250.
Clark, R. N., 2005. [Online]
Available at: http://www.clarkvision.com/articles/does.pixel.size.matter/
Foo, S. Y., 1996. A rule - based machine vision system for fire detection in aircraft dry bays and engine compartments. *Knowledge - Based Systems,* Volume 9, pp. 531 - 540.
Han, D. & Lee, B., 2009. Flame and smoke detection method for early real - time detection of a tunnel. *Fire Safety Journal* , pp. 951 - 961.
Healey, G. et al., 1993. A System for Real - Time Fire Detection. *IEEE,* pp. 605 - 606.
Heskestad, G., 2002. Fire Plumes, Flame Height, and Air Entrainment. In: *SFPE Handbook.* s.l.:Society of Fire Protection Engineers, pp. 2-3.
Horng, W. B., Peng, J. W. & Chen, C. Y., 2005. A New Image - Based Real - Time Flame Detection Method Using Color Analysis. *IEEE,* pp. 100 - 105.
Lai, C. L. & Yang, J. C., 2008. Advanced Real Time Fire Detection in Video Surveillance System. *IEEE,* pp. 3542 - 3545.
Lai, C. L., Yang, J. C. & Chen, Y. H., 2007. *A Real Time Video Processing Based Survillance System for Early Fire and Flood Detection.* Poland, IEEE.
Lee, D. & Han, D., 2007. Real - Time Fire Detection Using Camera Sequence Image in Tunnel Environment. pp. 1209 - 1220.
Li, Z., Khananian, A., Fraser, R. H. & Cihlar, J., 2001. Automatic Detection of Fire Smoke Using Artificial Nerual Networks and Threshold Approaches Applied to AVHRR Imagery. *IEEE Transactions on Geoscience and Remote Sensing,,* September, Volume 39, pp. 1859 - 1870.
Marbach, G., Loepfe, M. & Brupbacher, T., 2006. An image processing technique for fire detection in video images. *Fire Safety Journal,* pp. 285 - 289.

Mohd Shafry, M. R. et al., 2012. FiLeDl Framework for Measuring Fish Length from Digital Images. *International Journal of the Physical Sciences* , pp. 607 - 618.
Ono, T. et al., 2006. Application of neural network to analyses of CCD colour TV - camera image for the detection of car fires in expressway tunnels. *Fire Safety Journal*, pp. 279 - 284.
Otsu, N., 1979. A Threshold Selection Method from Gray - Level Histogram. *IEEE Transation Systems Man, and Cybernetics,* Volume SMC-9, pp. 62 - 66.
Owrutsky, J. C. et al., 2006. Long wavelength video detection of fire in ship compartments. *Fire Safety Journal*, pp. 315 - 320.
Podrzaj, P. & Hashimoto, H., 2008. Intelligent Space as a Framwork fr Fire Detection and Evacuation. *Fire Technology,* pp. 65 - 76.
Toreyin, B. U., Dedeoglu, Y., Gudukbay, U. & Cetin, A. E., 2006. Computer vision based method for real - time fire and flame detection. *Pattern Recognition Letters,* pp. 49 - 58.
Wang, S. J., Jeng, D. L. & Tsai, M. T., 2009. Early fire detection mehod in video vessels. *The Jurnal of Systems and Software*, pp. 656 - 667.
Wan, Y., Wang, J., Sun, X. & Hao, M., 2010. A Modified Otsu Image Segment Method Based on the Rayleigh Distribution. *IEEE*, pp. 281 - 285.
Yuan, F., 2008. A fast accumulative motion orientation model based on integral image for video smoke detection. *Pattern Recognition Letters,* pp. 925 - 932.
Zhang, D. et al., 2009. *Image Based Forest Fire Detection Using Dynamic Characteristics with Artificial Neural Network.* s.l., IEEE Computer Soceity, pp. 290 - 293.